An Extraction of Fatigue Damaging Events by Using Running Damage Extraction (RDE) Technique

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Abstract: - This paper presents the development of a new fatigue data editing technique, called Running Damage Extraction (RDE), for summarising long records of fatigue data. This technique is used to extract fatigue damaging events in the record that cause majority of the fatigue damage, whilst preserving the load cycle sequence. In this study, fatigue damaging events are identified from the characteristic of abrupt changes that exist in the fatigue data. Then, the events are combined to produce a mission signal which has equivalent statistics and fatigue damage to the original signal. The objective of this study is to observe the capability of RDE technique in summarising long records of fatigue data. For the purpose of this study, a collection of nonstationary data that exhibits a random behavior was used. This random data was measured in the unit of microstrain on the lower suspension arm of a car. Experimentally, the data was collected for 60 seconds at a sampling rate of 500 Hz, which gave 30,000 discrete data points. Global signal statistical value indicated that the data were non Gaussian distribution in nature. The result of the study indicates that this technique is applicable in detecting and extracts fatigue damaging events that exist in fatigue data.

Key-Words: - Abrupt changes, fatigue data, global statistics, nonstationary data, RDE technique,

1 Introduction

In fatigue data analysis, data editing plays an important role in calculating the damage that are caused by the stress loading. The function of fatigue data editing is to remove the small amplitude cycles for reducing the test time and cost. By using this approach, large amplitude cycles that cause the majority of the damage are retained and thus only shortened loading consists of large amplitude cycles is produced [1].

Previous studies have shown that several data editing technique has been developed for use in time domain. Some computational algorithms were developed to omit the small amplitude cycles as to retain the large amplitude cycles, such as: the application of local strain parameter and linear damage rule in selecting the edit levels of VA loading while retaining the original history in sequence, the use of a non linear damage rule incorporating overstrain and sequence effect, the use of a damage window joining function to produce an edited signal, the application of Smith-Watson-Topper (SWT) parameter to determine the range of low amplitude cycles that should be eliminated, bump extraction algorithm by using wavelet transform for summarising long record of fatigue data [2], and the application of Short-Time-Fourier-Transform (STFT) in removing low amplitude cycles to produce a shortened signal [3].

This paper discusses about a new technique that has been developed in extracting fatigue damaging events. The characteristics of this event are identified from the abrupt changes that exist in mechanical fatigue signal data. An abrupt changes is defined as the mean changes in characteristics that occur very fast with respect to the sampling period of the measurements, if not instantaneously. Since significant information contained in the measurement lies in their nonstationarities, and because of most adaptive estimation algorithms basically can follow only slow changes and very complex to understand, a new method are needed to be developed in detecting the abrupt changes that exist in the fatigue data [4]. In solving this problem, a new technique called Running Damage Extraction (RDE) method was proposed. This technique is designed to identify and extract fatigue damaging event that exist in variable amplitude (VA) loading data. This method was developed by combining the overlapping window concept and fatigue damage calculation. Later, this technique were expanded to be used in summarising the fatigue data by moving small amplitude cycles for reducing the time and cost. The goal of this study is to investigate whether this technique can be used accurately to shorten the typical fatigue histories data.

2 Literature Review

2.1 Signal Analysis

A signal is a series of number that come from a measurement, typically obtained using some recording method as a function of time. In real applications, signals can be classified into two types which are stationary and non-stationary behavior. A signal representing a random phenomenon can be characterised as either stationary or nonstationary behaviour. The stationary signals exhibit the statistical properties remain unchanged with the changes in time. On the other hand, statistics of non-stationary signal is dependent on the time of measurement. In the case of fatigue research, the signal consists of a measurement of cyclic loads, i.e. force, strain and stress against time. The observations of a variable were taken at equally spaced intervals of time [5].

In normal practice, the global signal statistical values are frequently used to classify random signals. In this study, mean, root mean square (r.m.s.) and kurtosis were used [6]. For a signal with n data points, the mean value of $\bar{x}$ is given by

$$\bar{x} = \frac{1}{n}\sum_{j=1}^{n} x_j \tag{1}$$

On the other hand, root mean square (r.m.s) value, which is the 2nd statistical moment, is used to quantify the overall energy content of the signal and is defined by the following equation:

$$r.m.s = \left\{\frac{1}{n}\sum_{i=1}^{n} x_j^2\right\}^{1/2} \tag{2}$$

where x_j is the j^{th} data and n is the number of data in the signal.

The kurtosis, which is the signal 4th statistical moment, is a global signal statistic which is highly sensitive to the spikeness of the data. It is defined by the following equation:

$$K = \frac{1}{n(r.m.s)^4}\sum_{j=1}^{n}(x_j - \bar{x})^4 \tag{3}$$

2.2 Fatigue Damage

It is common that the service loadings caused by machines and vehicles is evaluated using a strain-life fatigue damage approach [6]. The strain-life approach considers the plastic deformation that occurs in the localised region where fatigue cracks begin under the influence of a mean stress.

The total strain amplitude, ε_a is produced by the combination of elastic and plastic amplitude

$$\varepsilon_a = \varepsilon_{ea} + \varepsilon_{pa} \tag{4}$$

where ε_{ea} is the elastic strain amplitude and ε_{pa} is the plastic strain amplitude. The elastic strain amplitude is defined by

$$\varepsilon_{ea} = \frac{\sigma_a}{E} = \frac{\sigma'_f}{E}(2N_f)^b \tag{5}$$

while the plastic strain amplitude is given as

$$\varepsilon_{pa} = \varepsilon'_f(2N_f)^c \tag{6}$$

where σ_a is the stress amplitude, N_f is the number of cycles to failure, σ'_f is the fatigue strength coefficient, b is the fatigue strength exponent, ε'_f is the fatigue ductility coefficient, c is the fatigue ductility component and E is the modulus of elasticity.

Combining Equations 8 and 9 gives the Coffin-Manson relationship, which is mathematically defined as

$$\varepsilon_a = \frac{\sigma'_f}{E}(2N_f)^b + \varepsilon'_f(2N_f)^c \tag{7}$$

which is essentially Equation 7 above and is the foundation of the strain-life approach.

Some realistic service loads involve nonzero mean stresses. One common mean stress effect model is the Smith-Watson-Topper (SWT) strain-life model, which is defined by

$$\sigma_{\max}\varepsilon_a = \frac{\sigma'^2_f}{E}(2N_f)^{2b} + \sigma'_f\varepsilon'_f(2N_f)^{b+c} \tag{8}$$

and the damage parameter is taken to be the product of the maximum stress and the strain amplitude of a cycle. In our study the strain-life approach and the Smith-Watson-Topper (SWT) strain-life model for mean stress effect were used in all fatigue damage calculations.

Fatigue damage is derived from the number of cycles to failure where the relationship is

$$Damage = \frac{1}{N_f} \tag{9}$$

and therefore fatigue damage values have the range [0, 1] where zero denotes no damage (extremely high or infinite number of cycles to failure) and 1 means total failure (one cycle to failure).

The RDE plot in this study has many non-parallel lines that contain a significant number of local optima, which can be classified as either peaks or valleys. A peak is defined to be associated with change in the slope from positive to negative, while a valley is associated with a change in the slope from negative to positive [7]. Peaks in a RDE are essentially the local maxima and valleys are the local minima. Depending on the resulting RDE, some points can be classified as neither peaks nor valleys.

Peak-Valley (PV) identification can be used to segment signals so that each segment may contain certain numbers of peaks and/or valleys, according to the needs of the study. This is particularly useful for fatigue time series data, since peaks and valleys feature predominantly in rainflow counting algorithms for fatigue damage calculations [8]. PV-based techniques are also used in mechanical modeling [9], quantifying roughness of materials [9, 10, 11], and image segmentation [12].

2.3 Fatigue Signal Segmentation

In signal processing, a segmentation algorithm were used to splits the signal into homogenous segments, the lengths of which are adapted to the local characteristics of the analyzed signal. The homogeneity of a segment can be in terms of the mean level or in terms of the spectral characteristics [1]. In fatigue life assessment study, fatigue signal extraction is described as a method to summarise a fatigue signal.

The first step of summarizing the fatigue signal is to isolate the low and high amplitude events in different segmentation. All the extracted segments (the complete section between the start and the end of the segments) are selected based on peak and valley time location of the running damage values.

3 Methodology

The data that was used in this study is variable fatigue strain loading data. It was collected from an automobile component during vehicle road testing. It was obtained from a fatigue data acquisition experiment using strain gauges and data logging instrumentation.

The collected fatigue data were measured on the car's front lower arm suspension as it was subjected to the road load service. All the data that were measured from this experiment are recorded as strain time histories.

The strain value from this test was measured using a strain gauge that was connected to a device, a data logger for data acquisition. Experimental parameters that need to be controlled in this test such as sampling frequency and type of output data being measured were specified in a data acquisition software.

In order to collect a variety of data, the car was driven on three different road:- pave route, highway and campus roads.

Experimentally, the data was collected for 60 seconds at a sampling rate of 500 Hz, which gave 30,000 discrete data points. This frequency was selected for the road test because this value does not cause the essential components of the signal to be lost during measurement. The road load conditions were from a stretch of highway road to represent mostly consistent load features, a stretch of brick-paved road to represent noisy but mostly consistent load features, and an in-campus road to represent load features that might include turning and braking, rough road surfaces and speed bumps.

As to fullfill the main purpose of this study, the RDE algorithm is used to identify and extract the abrupt changes for fatigue damaging events. This technique is based on the running concept which the original data are separated by using overlapping window. For a signal with n data points, the numbers of overlapping window is given by $x_i \in X$, where X is the signal data, h is the size of overlap and m is the size of the window

$$\{ x_j , x_{j+1} , x_{j+2} ,..., x_{j+k-1} \}, \tag{10}$$

where

$$i = 1,2,3,...$$
$$j = 1,1+h,1+2h,...$$
$$k = m,m+h,m+2h,...$$

A flowchart describing the RDE technique is presented in Fig. 1 and it involves with several stages: the input signal and global statistics parameter; transform input signal into overlapping window; calculation of running damage based on the overlapping window; identification of optimized running damage; the identification and extraction of abrupt changes for fatigue damaging events; and decision making process.

The first stage of RDE algorithm is to display the three different types of fatigue data in times series plot and global statistic parameter. In normal practice, the global signal statistical values are frequently used to classify random signals. In this study, mean, root mean square (r.m.s.) and kurtosis were used [2].

The next stage is the most crucial part in the development of RDE techinque. At first, the data was divided in different window by using the overlapping algorithm. In each window, there are 500 data points. The data points in each window that consist of original data were then overlapped between each other from 10% to 90%. Then, the data that was produced in each window was transferred into Glyphwork software for calculating the value of fatigue damage. The purposed of overlapping in this study was based on the assumption to reduce the possibility of damaged calculation for each window that crosses over the peak values in the original signal.

Then, the identification of optimised running window was needed. Each overlapping window for running damage was plot over time. Regression analaysis is proposed to be used in analyzing the variation component in the running damage data. The trend values for the running damage were then compared to the trend values of original signal. In this study, it is proposed that the optimum value for overlapping running damage be based on the minimum values of trend analysis as it represents the removal of the trend component from the actual data.

The third stage of the RDE algorithm is to identify and extract the abrupt changes for fatigue damaging events. In this stage, the RDE was combined with peak and valley calculation so that the decision function for the time series segmentation can be performed. The identification for abrupt changes in the original signal was based on the method of searching of wave bump extraction. The reference about this method of searching can be referred from this article [2]. The low and high amplitude events in the original signal were isolated in different segmentation.

A new parameter which include zero damage value in the segmented data, which represents the uncritical part in fatigue signal behavior that are needed to be removed from the original signal was set. This means that, the segmented data that has high impact of damage will be retained and the segmented data that has zero impact of damage will be eliminated. Thus, a new shortened edited signal which neglected low amplitude cycles is produced

The last stage involve with the identification on whether the RDE algorithm can detect transient events in fatigue data. It is assumed that the RDE algorithm can be used in predicting the abrupt changes that exist in fatigue data.

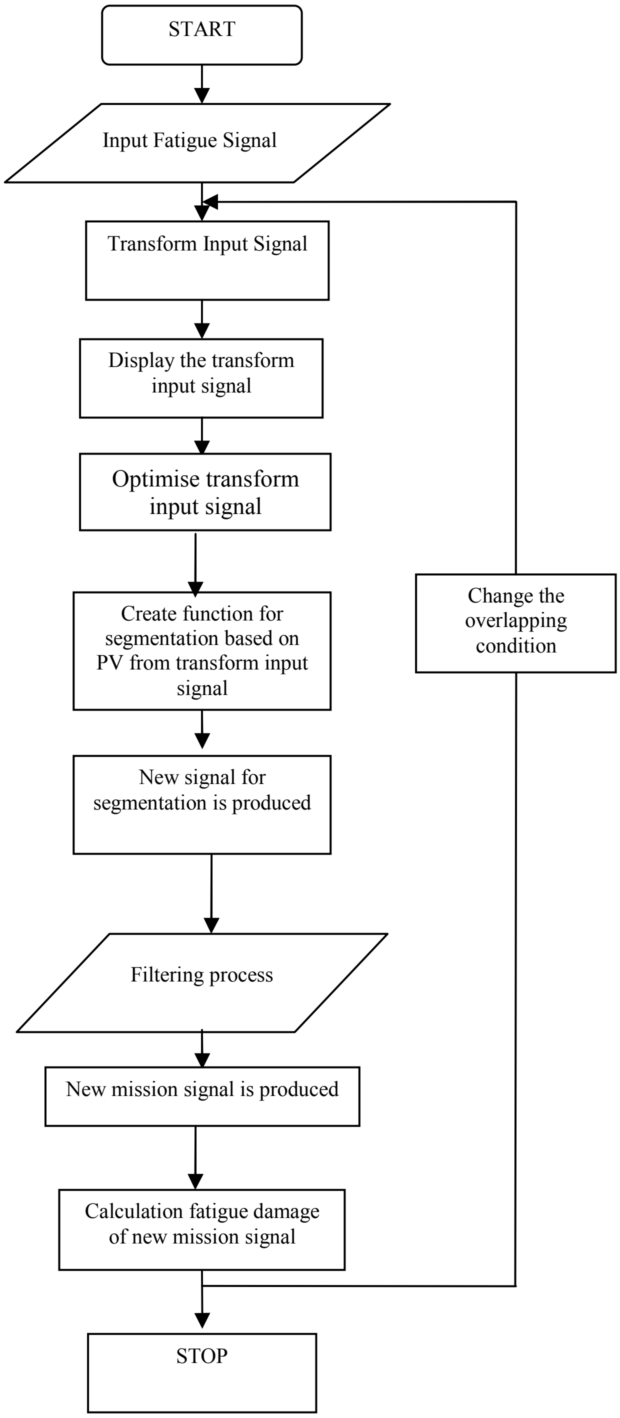

Fig. 1: The RDE method flowchart

For validation purposes, the fatigue damage potential for both original and edited signals were calculated in order to study the efficiency of the edited signal based on the fatigue damage retention. In order to retain the originality of the signal, the statistical parameter of the edited signal need to be equivalent to the original signal. For this case, the 10% difference in the root-mean-square and kurtosis values between the edited and the original signals was used for analyzing experimental road load data sets. This is important in order to retain the signal energy and amplitude ranges [3, 18].

4 Results and Discussion

From the result, the optimum condition for overlapping window for case study data which is 80% shows a significant result in extracting fatigue damaging events. All of the edited signals gained from the zero value of damage were retained in the majority of the fatigue damage and were approximately same as the original signal and they also retained the statistical parameters with below that 10% deviation.

Figure 3, 4 and 5 represent the original and edited signal for Pave route, highway and campus signals respectively.

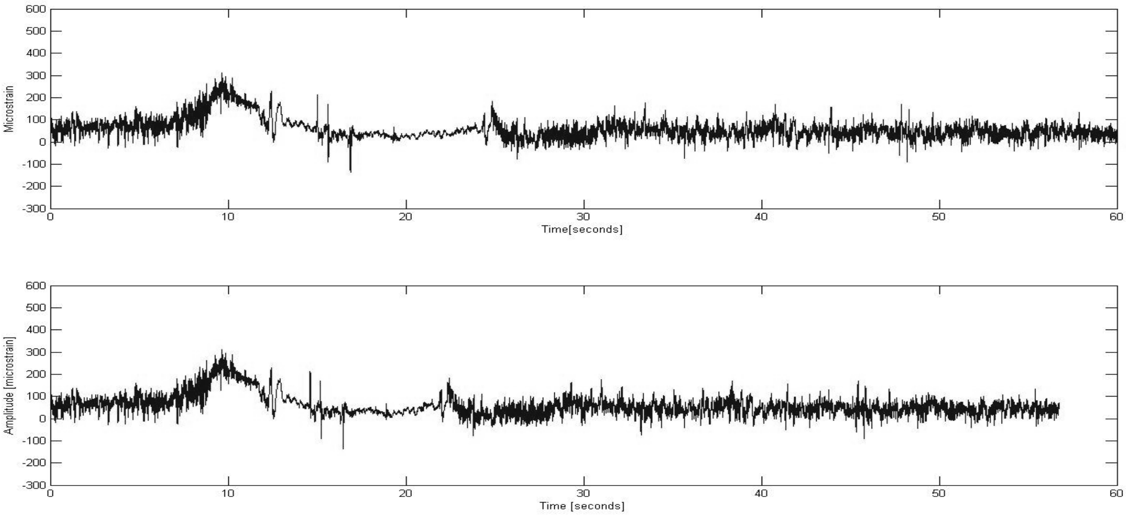

Fig.2: Comparison between the original and edited signal for Pavé Route data

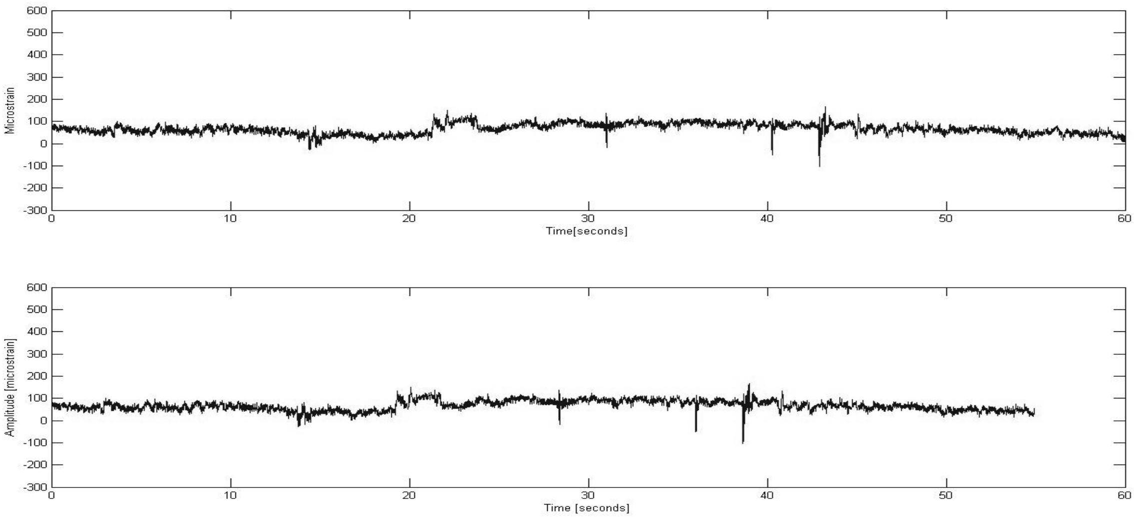

Fig.3: Comparison between the original and edited signal for Highway data

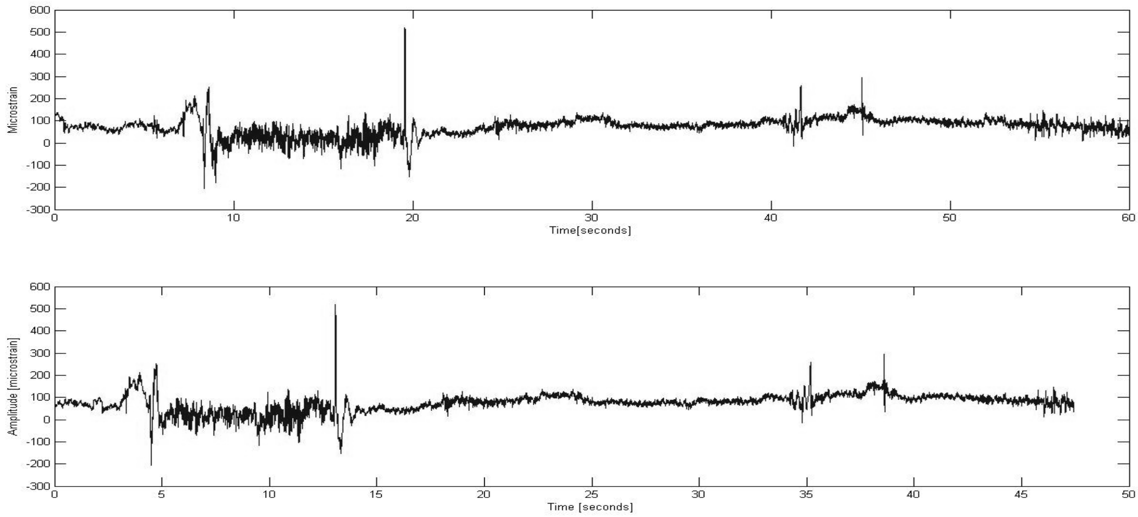

Fig.4: Comparison between the original and edited signal for Campus data

From all the figures above, it was shown that the high amplitude events were retained in edited signal. The compression characteristics between the original and the edited signals were shown in Table 1. In overall, the analysis of this study suggested that the RDE technique fatigue data editing can successfully remove the low amplitude cycles while retaining the characteristics of original behaviour. With the basis of the statistical parameter retention between the original and the edited signals, this technique produced the highly accurate signal which was similar to the original signal. The RDE plot shows relatively adequate with damage event in the fatigue signal and is a very useful tool for damage detection in the fatigue data analysis. The extraction of damaging events successfully created a new edited signal which retained the majority of fatigue damage

Data	Signal Length (seconds)	Mean	RMS	Kurtosis	Damage
Original Pave	60	58.22	74.53	6.7	5.78E-03
Edited Pave	56.7	59.14	75.82	6.41	5.74E-03
Original Highway	60	66.32	70.3	3.58	5.13E-04
Edited Highway	54.9	66.46	70.27	3.89	4.94E-04
Original Campus	60	72.48	83.34	10.53	7.37E-03
Edited Campus	47.4	74.31	85.52	10.77	6.71E-03

Table 1: The Compression characteristics between the original and the edited signal

5 Conclusions

This study discussed about the capability of a fatigue data editing technique in time domain by using Running Damage Extraction (RDE) method. This technique was developed to remove the low amplitude cycles which were contained in the original signal. From the analysis, the editing process was performed based on the filtering parameter which eliminated the segment that contained zero values of damage. In the presented case study data, i.e., the Pavé edited signal, the highway edited signal and campus edited signals have the same length with the reduction of 5.5%, 8.5% and 21% respectively from the original signal. All signals also retained the major signal statistics with below than 10% of the root-mean-square value (representing the vibration signal energy in a time series) and the kurtosis value (representing the amplitude range in a time series). Although this technique can shorten the original signal from the case study, a validation of the effectiveness of this method needs to be done. The validation step needs to be taken in order to make sure the robustness of this technique as an alternative in fatigue durability study, especially for the automotive engineering field would not be disputed.

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